

The Effect of Pokémon Go on The Pulse of the City: A Natural Experiment

Eduardo Graells-Garrido*, Leo Ferres, and Loreto Bravo

Data Science Institute, Faculty of Engineering, Universidad del
Desarrollo, Santiago, Chile.

Telefónica R & D, Santiago, Chile.

Pokémon Go has received unprecedented media coverage for a location-based game that uses augmented reality techniques. The game has been commonly associated with greater access to public spaces, increasing the number of people out on the streets, and generally improving health, social, and security indices. However, the true impact of Pokémon Go on people's mobility patterns in a city is still largely unknown. In this paper we perform a natural experiment using data from mobile networks to evaluate the effect of Pokémon Go on the pulse of a big city: Santiago of Chile. We found a significant effect of Pokémon Go on the floating population of Santiago: up to 13.8% more people being outside at certain times, even if they do not seem to go out of their usual way. These effects at specific times were found by performing several regressions using count models over snapshots of the cell phone network. The effect is significant after controlling for land use, daily patterns, and points of interest in the city. Particularly, we found that, in business days, there is more people on the street at commuting times, meaning that people did not change their daily routines but slightly adapted them to play the game. Conversely, on Saturday and Sunday night, people indeed went out to play to places nearby their homes. Even if the statistical effects of the game do not reflect the massive reach portrayed by the media, it still allowed the streets to become a new place for people to spend time in. This is important, because results like these are expected to inform long-term infrastructure investments by city officials, jointly with public policies aimed at, for example, stimulating pedestrian traffic or suggesting alternative routes. Our work supports the notion that location-based games like Pokémon Go have benefits for the life in the city.

1 Introduction

Pokémon Go has become a world-wide hit. People of all ages seem to be caught in the frenzy of walking everywhere trying to find the next pocket monster. This has resulted in everything from making kids move out of the living room and into the open air, to governments issuing alerts on playing the game in minefields,¹ of searching Pokémon in “inappropriate” places like the Holocaust Museums and the White House² or even to causing accidents.³

*egraells@udd.cl.

¹<http://goo.gl/AvjpGL>

²<http://goo.gl/TWeI86>

³<http://goo.gl/d69rjS>

The way people are living their cities is hard to change, and problems affecting cities like safety and transportation issues are diminishing their quality of life. The public policy changes and the concrete actions needed to improve cities often are discarded due to their long-term implementation times and short-term political views by city governors. Yet, Pokémon Go has initiated a wave of change. Its success and the need to find alternate ways to induce behavioral change, in terms of how a city is lived by its citizens, motivates the research in this paper.

The general perception is that games like Pokémon Go and its predecessor, Ingress [30], among other similar albeit less famous ones like PacManhattan [25], could make whole populations change their mobility patterns through a reward-system: earning more points by catching creatures, getting to certain places and checking in, among other well-known gamification techniques. Ingress and Pokémon Go have a laxer definition of “check-points” than a city’s usual Points of Interests (POIs, like museums and parks) including, for example, graffiti [33] and hidden heritage [49]. This means that these games motivate visiting *different* places, even when comparing to POIs available in other games or gamified platforms like FourSquare.⁴ Because people tend to visit few POIs in their daily routines [38], this implies that people would tend to visit different places from those they would visit before. If this is in fact the case, and considering that Pokémon is one of the most successful media franchises in the world [5], providing empirical evidence in favor (or against) this folk hypothesis would help understand the level to which these games make people change their habits. Particularly, we ought to seek the usage of data science tools to quantify the *Pokémon Go Effect* on the pulse of a city, as seen from its floating population patterns.

Objectives and Approach. Floating population is the concept used to denote the number of people on a given area that stays on it during a specific period of time, but that does not necessarily reside there. For instance, people who work in a business district is part of its floating population, but they reside elsewhere. Having this concept in mind, and the successful launch of Pokémon Go, our research question is: *Is there any effect on a city’s floating population patterns induced by Pokémon Go at the city-scale? What are its characteristics?*

In Chile, Pokémon Go was officially launched on August 3rd, 2016. The base for our analysis is a set of mobile communications records from Telefónica Movistar, the largest telecommunications company in Chile, with a market share of 38% in 2015. Particularly, we use a dataset that follows the Call Detail Records structure, *i.e.*, it is a dataset built by the company for billing purposes. CDR datasets usually include logs of phone calls, SMS’, and data-type network events (*e.g.*, Web browsing, application usage, etc.), aggregated by context-dependent amount of downloaded information [9]. Thus, even though we cannot identify who is playing the game on the dataset, external reports indicate that after five days of the launch, one million people downloaded the game.⁵

To answer our research question, we follow a natural experiment approach whereby we evaluate floating population patterns at two specific intervals of time: the seven days before and the seven days after the launch of Pokémon Go. Particularly, we do so using data-type mobile data records from Santiago, the capital of Chile. We select a specific number of devices, to ensure that we analyze floating population patterns of active users that live on the city. Then, using regression models suitable for count data, we evaluate whether the launch of the game had impact on the floating population. Given that we restricted the set of studied users, and that we assume that a higher number of connected mobile devices means a higher number of people on the street, the regression analysis gives us a quantitative measure of the effect of the game. Finally, we explore how the significant effects relate with urban mobility by graphically correlating their characteristics with travel surveys and the availability of points of interests.

Main Findings. Our main results are as follows:

- There is a significant effect of the availability of Pokémon Go in Santiago’s floating population patterns, including covariates that account for daily patterns, land use, and available points of interests. Particularly, the highest effect at business hours is found at 12:31, with 13.8% more people connected to mobile networks. After business hours, the strongest effect is found at 9:31pm, with 9.6% of more people connected to mobile networks.
- In business hours the effects are significant in commuting times between important places (like *home* and *work*) and break hours (*e.g.*, lunch times). Since there are small but significant differences in the

⁴<http://foursquare.com>

⁵<https://goo.gl/T2pthM>

area covered by users through their mobility, measured through their daily radius of gyration, people adapted their routines to play the game. This is also noticeable on the map, as the effect is concentrated in places with high floating population.

- Unlike effects at business hours, at night places with Pokémon Go players are scattered around the city. This hints that people played the game at night in places near their homes, at times they were usually in indoor contexts.

Contributions. The contributions of this work are two-fold. First, we present methods and techniques to analyze mobile records that allow to identify behavioral change at the city level, using regression models and mobility metrics. Second, we contribute a case study on a city from a developing country: Santiago of Chile, and report empirical insights on the observed phenomena. To the extent of our knowledge, this is the first large-scale study on the effect of location-based augmented reality games on the pulse of a city.

Moreover, in addition to mobile datasets, we use datasets that are usually available, like travel surveys, and, if they were not available, can be approximated using mobile data. Hence, the methods presented on this paper can be used to perform a similar analysis in other cities, as well as monitoring how much a change in behavior lasts. Finally, we translate our findings into practical and theoretical implications in the areas of urbanism and social life on the city.

2 Data and Methods

We focus our study on Santiago, the capital of Chile. Santiago is the most populated city in the country, with almost 8 million inhabitants, more than one third of the country’s population. With a surface of 867.75 square kilometers, the metropolitan area of Santiago is composed of 35 independent administrative units called municipalities. The city has experienced accelerated growth in the last few decades, a trend that has been predicted to continue at least until 2045 [40]. Chile, and Santiago in particular, is one of the developing regions of South America with the highest mobile phone penetration. There are more mobile subscriptions than inhabitants, with about 132 mobile subscriptions per 100 people.⁶ Santiago’s growth and availability of mobile phones makes it a good city to perform research based on mobile communication data.

2.1 Datasets

The studies we report make use of several complementary datasets that we describe below:

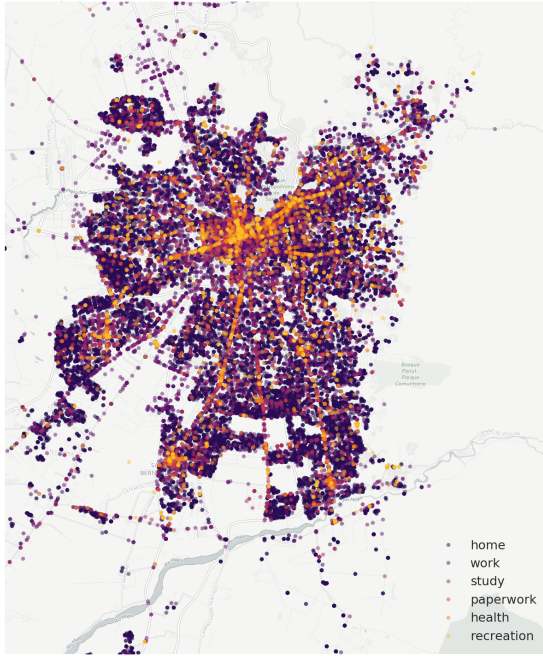
Santiago Travel Survey and Zonification. The Santiago 2012 Travel Survey⁷ (also known as Origin-Destination survey, or ODS) contains 96,013 trips from 40,889 users. Figure 1 (a) shows the destination point of each trip in the city, colored according to the purpose of the trip. The results of the survey are used in the design of public policies related to transportation and land use. The survey includes zoning limits of the entire Metropolitan Region, encompassing Santiago and nearby cities. We use this zoning method for three reasons: first, each area within a zone takes into account population density. Thus, it is possible to compare phenomena between zones. Second, it allows us to integrate other sources of information, providing results that can be compared to other datasets such as land use properties [20]. Note that zones respect administrative borders, as well as great avenues and natural separations (*e.g.*, rivers, hills, etc.). Third, antenna coverage is not constant in time. Everyday several antennas on the cell towers are calibrated. Moreover, some antennas are turned off during specific hours of the day.

The complete dataset includes 866 zones; however, we are interested in urban areas of a single city. Since these are densely populated, we restrict our analysis to zones with a surface of under 20 Km². As result, the maximum zone area is 18.37 Km², with mean 1.34 and median 0.72 Km². Finally, we are interested in zones that have both cell phone towers and Pokémon points of interests (see Figure 1), resulting in 499 zones covering 667 square kilometers. Figure 1 (c) shows these zones and the municipalities they belong to.

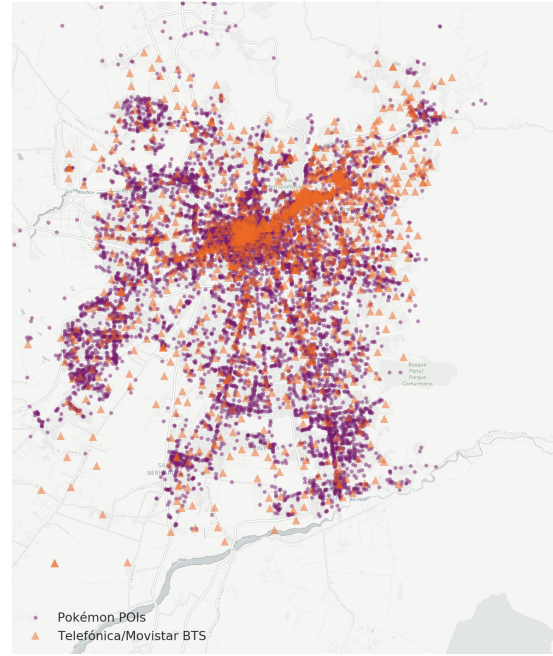
Pokémon Points of Interest / Ingress Portals. Ingress [30] is a location-based game launched by Niantic Labs in 2012. In the game, players choose one faction (from two available), and try to hack several *portals*

⁶<https://goo.gl/sjWEjS>

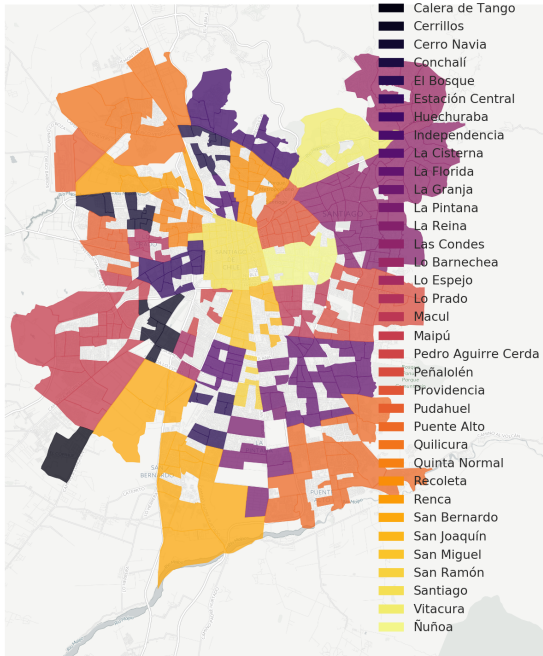
⁷<https://goo.gl/vStth8>.



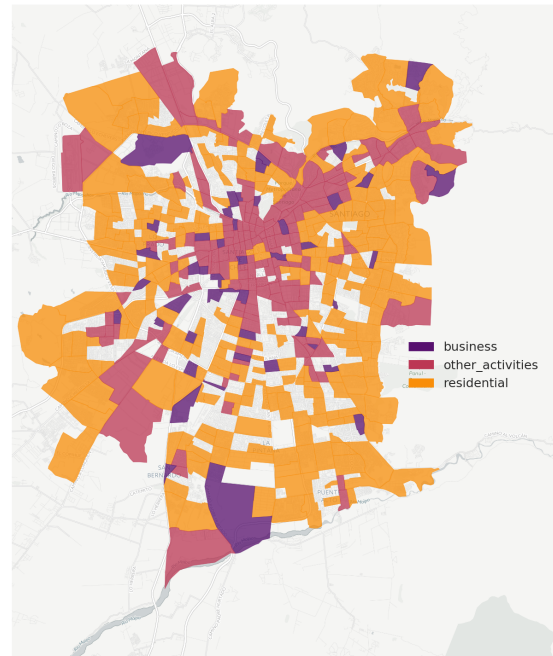
(a) Trip Destinations from Travel Survey.



(b) PokéPoints and Telefónica Cell Towers.



(c) Municipality OD Zones.



(d) Zone Clusters from Floating Population.

Figure 1: Maps showing the spatial characteristics of the datasets used on the study. On the top row: the trip destinations from the Santiago Travel Survey 2012 ((a)); the Telefónica cell tower stations and Pokémon points of interests in Santiago ((b)). On the bottom row: OD zones from the travel survey used on the study, colored according to their municipalities ((c)) and their land use clusters ((d)) estimated from mobile records. Note that maps (c) and (d) show only the OD zones that contain both, cell towers and PokéPoints. Background tile data was provided by ©OpenStreetMap contributors and ©CartoDB.

placed in real locations world-wide. Portals are crowd-sourced and include “a location with a cool story, a place of historical or educational value”, “a cool piece of art or unique architecture”, “a hidden-gem or a hyper-local spot”, among others.⁸ The definition of a portal, thus, includes very hyper-local points that may not be available in, for instance, check-in based social networks [33]. Once a portal is hacked, it belongs to the corresponding faction. A set of portals belonging to the same faction defines the limit of an area controlled by it. Since players need to be close to portals to hack them, this makes players explore the city to find portals to hack and conquer for their own factions.

Pokémon Go, launched in 2016 and also by Niantic Labs, shares many game mechanics with Ingress, including the faction (“team”) concept. The main difference is that in Ingress players capture portals, while in Pokémon Go they capture wild pocket monsters. A subset of Ingress portals is defined to be a PokéStop (a place to check-in and get items) or a PokéGym (a place to battle against the Pokémon of other factions). In this paper, we refer to both as PokéPoints. Additionally, there are Pokémon respawn points, where different creatures tend to appear. However, those points are hidden from players, who must walk around and explore to find creatures to capture. Note that all players see the same creatures, and one creature may be captured by many players. Figure 1 (b) shows the Pokémon points of interest on the city (Pokéstops and Gyms).

Cell Phone Towers in Santiago. Telefónica has 1,464 cell phone towers in the municipalities under consideration (see Figure 1 (b)). Because of demand, antennas tend to be installed in places with high floating population, *i. e.*, places with primarily work and study trip destinations, as seen on Figure 1 (a). Formally, tower distribution is rank-correlated with the ODS destinations at municipal level ($\rho = 0.91, p < 0.001$) [20].

Mobile Communication Records. We study an anonymized Call Detail Records (CDR) dataset from Telefónica Chile. The dataset contains records from the seven days prior to the launch of Pokémon Go (from July 27th to August 2nd) and the seven days after (from August 4th to August 10th). Note that we do not take into account the day of the official launch of Pokémon Go, as there is no specific hour in which the game was officially available. Also note that the dataset contains both, pre-paid and contract subscriptions.

A record from our dataset has the following format:

```
date,                                     hash,  time,  tower,  size
160727, 000380e9a23ab8dfdba438e683e167d7, 62200, LOMIR, 76
```

We use data-type rather than voice CDRs. Unlike typical Call Detail Records for voice, each data event has only one assigned tower (LOMIR in the example above), as there is no need for a destination tower. The size of the event indicates the number of KiB downloaded since the last registered event. Note that not all companies register their events in the same way for billing purposes. In our case, these records follow a periodic update, which is “generated on a periodic base and provides information on which cell tower the phone is connected” [9].

We do not analyze the records from the entire customer population in Santiago. We apply the following filtering procedure: first, we filter out those records that do not fall within the limits of the ODS explained above and also those with a timestamp outside the range between 6:00am and 11:59pm. In addition, to be considered, mobile devices must have been active every day under study. This is needed because a device that does not show regular events may belong to a tourist or someone who is not from the city. Finally, only devices that downloaded more than 2.5 MiB and less than 500 MiB per day are included, as that indicates either inactivity or an unusual activity for a human (*i. e.*, the device could be running an automated process). After these filters, the dataset comprises records from 142,988 devices. In other words, every measure is taken to ensure that events are triggered by humans.

An assumption is that network events are triggered when devices are on the street. Characteristically, significant places (*e. g.*, house and the workplace) tend to have WiFi networks and devices would connect to them.⁹ Thus, for instance, when comparing two different days at a specific time, an increase in the number of connected devices would mean that there are more people on the street.

Land Use Clusters. This study uses three different categories of land use: residential areas, business areas, and areas with mixed activities (*e. g.*, recreation, shopping activities, among others). The categorization is

⁸<https://goo.gl/4QHtBQ>

⁹72% of homes have Internet access according to the last survey of telecommunications <https://goo.gl/bwyzPG>.

shown on Figure 1 (d). These categories are the result of our previous work on land use based on CDR data [20].

2.2 Approach

We seek to measure the Pokémon Go effect at the city scale using a natural experiment approach. To do this, we analyze the change in population patterns before and after the launch of Pokémon Go as evidenced by CDR data. First, we describe a method of smoothing the number of connected devices at each cell tower according to several snapshots of the tower network. A snapshot is the status of the cell phone network in a given time-window [34]. Then, we aggregate these device counts at the zone level. These aggregated counts define a set of observations that we evaluate in a regression model, taking into account covariates that allows us to isolate and quantify the Pokémon Go effect.

Smoothed device counts at each tower and zone level aggregation. Let $e \in E$ be a network event, and $|E|$ is the total number of such events. A network event e is a tuple (d, u, b, z) , where d is a timestamp, u is some (anonymized) user, b is a tower id, and z is one of the previously defined geographical areas of Santiago. Then, for each tower b , and time d we build a time-series $B_{d,b}$ which represents the number of unique users from E connected to b at d . Then, we perform a LOWESS (*Locally Weighted Scatterplot Smoothing*) interpolation [12] over the time-series. This allows us to smooth noise and drastic changes in the number of connected devices in consecutive intervals of time, as well as to interpolate the number of network events between minutes. This is needed because CDR data is sparse. Finally, we aggregate these counts at the zone level in a time-series $S_{d,z}$ by adding all time-series B_{d,b_i} , where b_i lies in z , determined using a point-in-polygon test (similar to [31]). The S time-series represents the daily population profile for each zone and each day under study.

Measuring the Pokémon Go effect using regression. We measure the city-wide Pokémon Go effect using several Generalized Linear Model regressions [35] over 1-minute snapshots of floating population profiles. That is, for every minute under study (*i.e.*, from 6am till midnight) we perform a Negative Binomial Regression [21] (NB, hereafter) using the observations within that snapshot across every day under study. The NB regression model has been used frequently to analyze over-dispersed count data, *i.e.*, when the variance is much larger than the mean, contrary to the Poisson model [10]. We seek to predict the number of connected users based on the availability of the game, the characteristics of the zone, and the day of the week. The proposed model is specified as follows:

$$\log E[X(t)] = \log a + \beta_0 + \beta_1 \text{PoGo} + \beta_2 \text{DayOfWeek} + \beta_3 \text{LandUse} + \beta_4 \text{PokéPoints},$$

where $E[X(t)]$ is the expected value of the number of active devices within a zone at time t . The PoGo factor represents the availability of the game, a binary variable taking a value of 0 for days before 2016-08-03 and 1 for days after 2016-08-03. As covariates, DayOfWeek (with values *business*, *saturday*, and *sunday*) and LandUse (with values *residential*, *business*, and *other_activities*) account for the fluctuations in population on different days according to land use. PokéPoints represents the number of Pokémon points of interest within a given zone. This last covariate accounts for the number of potential attracting places in each zone. We specify the surface area a of each zone as exposure in the model. Note that we used dummy coding for the categorical factors DayOfWeek and LandUse.

The NB regression allows the following interpretation: the β coefficient assigned to a factor represents the difference of the logarithm of expected counts in a zone at time t , if all other factors were held equal. Since $\beta = \log \mu_1 - \log \mu_0 = \log \frac{\mu_1}{\mu_0}$, then difference of logarithms equals the logarithm of the ratio between population counts after and before the availability of the game. The exponential of this coefficient is defined as Incidence Rate Ratio, $IRR_\beta(t) = e^{\beta(t)}$. Then, we build a time-series of $IRR_\beta(t)$ values for each factor. By inspecting these time-series we determine when, in terms of time-windows within a day, there is a significant effect of each factor.

Mobility metrics. To explore whether Pokémon Go expanded the area covered by people in their daily routines, we analyze the radius of gyration r_g , which has been used before to characterize human mobility [18]. This radius is defined as:

$$r_g = \sqrt{\frac{1}{n} \sum_i^n |r_i - r_{cm}|^2},$$

where n is the number of events for a given device, r_i is the position of a particular event generated by the device, and r_{cm} is the center of mass for the device. The center of mass is defined as the average tower position of all network events of a mobile device. Particularly, we estimate the daily d of r_g for all users, every day, and interpret accordingly.

3 Case Study: The Effect of Pokémon Go in Santiago, Chile

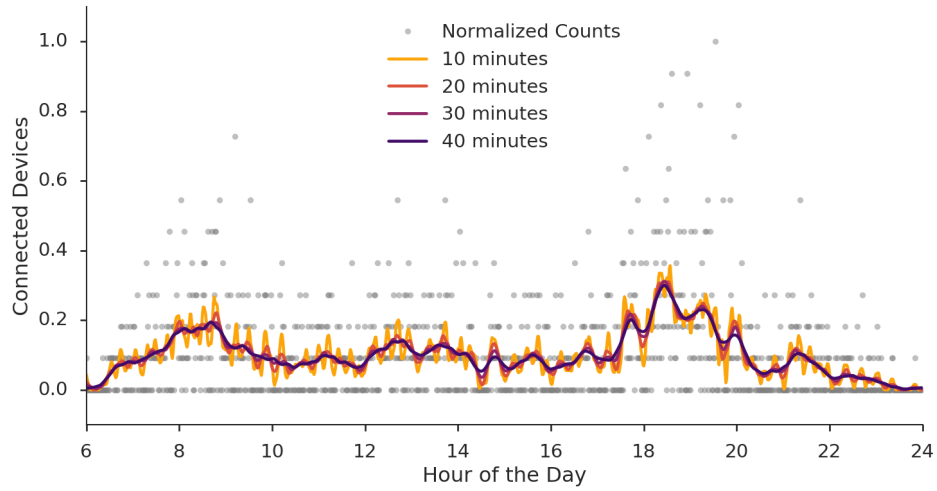
Our aim is to measure the effect of Pokémon Go in the number of people and their mobility patterns in a city. As stated in our methods, the first step is to obtain a smoothed number of connected devices per minute to each tower. Figure 2 (a) shows the normalized number of events per minute in a specific tower (Moneda Metro Station) during July 27th. One can see that many times of the day (in minutes) do not have registered events (gray dots at 0 in the y -axis), even though the tower is located in a business area with a high rate of public transportation traffic. We used LOWESS interpolation to fill the gaps in the data. The continuous lines in Figure 2 are LOWESS interpolation calculations considering values of 10, 20, 30 and 40 minutes for the LOWESS time windows. Visually, a time window of 30 minutes seems enough to capture interesting regularities without incurring in noise produced by the sparsity of the data.

Figure 2 (b) shows the aggregation of towers within Zone 18, including the tower shown in Figure 2 (a). One can see that the LOWESS curve faithfully represents the population profile for the zone: the curve for zone 18 exhibits a profile similar to those expected from business-oriented areas [20, 26].

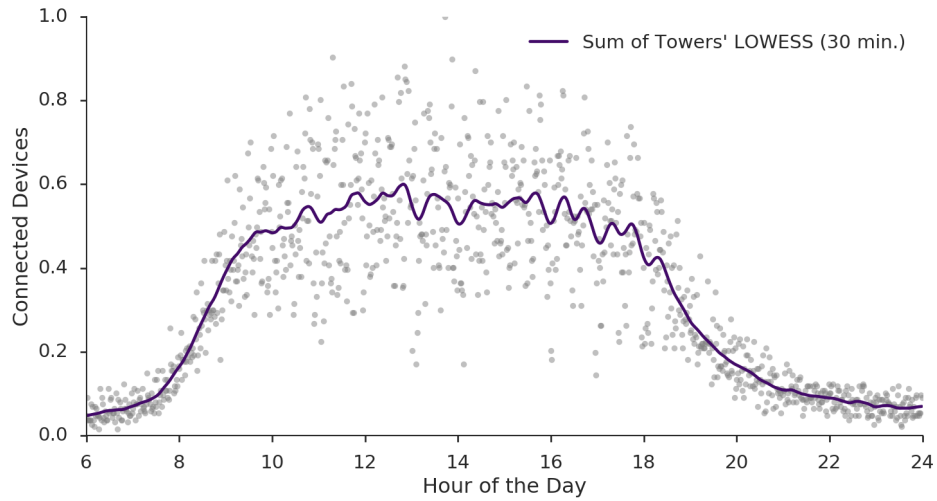
City-level connections. Figure 3 shows the city-level aggregated number of connected devices, having three categories of days: *before*, *during*, and *after* the launch of Pokémon Go. One can see that, although the curves tend to have similar shapes, after the launch of the game the number of connected devices is often greater. The patterns are stable across most days, with the means for connections generally higher when Pokémon Go was available. This means, intuitively, that there were more people connected to the network, presumably playing the game. Two rather surprising effects are found in Mondays between 10am and 12pm when Pokémon Go was available, and Tuesdays at about 12pm when it was not yet available. In the first case, we hypothesize that since it was the first Monday after the launch of the game, people were trying it out. In the second case, there does not seem to be any explanation for the sudden drop of connections before the launch of the game, but it might be due to general network outages. Notice that the curve for when Pokémon Go was available in the same time period, the curve behaves as expected. Finally, a word should be said about Saturdays. The first Saturday after the release of Pokémon Go exposes the highest number of device connections found in the dataset. While it is tempting to associate this effect to other extraneous factors (for example, the Olympic Games were on TV in those days), our method shows that indeed part of those connections can be associated to the Pokémon Go factor.

Negative Binomial Regressions. After aggregating the smoothed counts for each zone, we performed a NB regression for every 1-minute snapshot across the days in our dataset. In other words, for each minute, the observations are the aggregated zone counts for all days, for all zones, at that specific minute. As result, we obtained a time-series of regressions representing the dynamics of each factor in our model. Figure 4 shows the Incidence Rate Ratios (IRR) for each factor, as well as the distribution of model dispersion (α). The significance of each factor is determinated according to their 95% confidence intervals, which should not intercept 1. The day of week covariates captured behavior expected for the weekends. There is less people (IRR is significantly lesser than 1) in the morning for both kind of days, and Saturdays exhibit part the effect mentioned before with an IRR of 1.278 at 9:59pm. The land use covariates captured the dynamics of high floating population during the day, given the bell-shape of their distributions, and that their IRRs are significant during the whole day. The PokéPoints covariate, which is a proxy for points of interest in the city, is also significant during the whole day. Its maximum IRR is 1.019, which means that for every additional POI in a zone, the amount of people increases by 1.9%, if all other factors are held equal when performing the comparison.

Having analyzed the other factors, we now analyze the time windows where the Pokémon effect is significant. Table 1 summarizes these time windows. Most of them, while significant, are few minutes long. However, there are some windows with prominent lengths: from 11:58 to 12:46, and from 21:24 to 22:12. These two time windows also contain the highest IRR values found per window: 1.138 and 1.096,



(a) Cell Tower: Moneda Metro Station.



(b) Floating Population Profile for Zone 18: Plaza Constitución and Palacio La Moneda.

Figure 2: LOWESS interpolations of the number of connected devices.

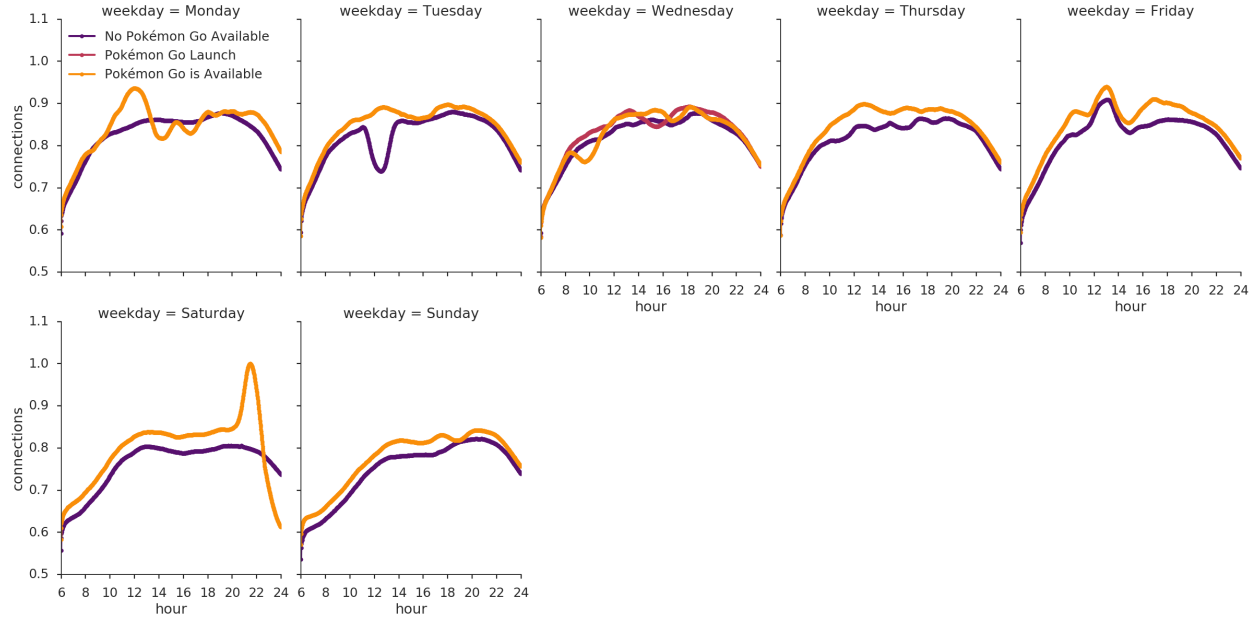


Figure 3: Amount of connected devices to the network in KiBs ((b)), per minute, for all days in the dataset. Note that the distributions are normalized by dividing the actual number of connections by the global maximum value. This is done to avoid publishing sensitive business information and for anonymization purposes.

Table 1: Pokémon Go effect time windows.

Time Window	Max IRR	Time of Max IRR
6:34 – 6:47	1.062	6:40
7:07 – 7:18	1.056	7:11
7:37 – 7:46	1.054	7:42
7:48 – 7:48	1.047	7:48
9:35 – 9:43	1.060	9:40
10:27 – 10:41	1.077	10:34
10:53 – 11:18	1.071	11:07
11:58 – 12:46	1.138	12:31
13:06 – 13:09	1.051	13:08
15:36 – 15:51	1.058	15:50
16:17 – 16:21	1.052	16:19
18:30 – 18:34	1.052	18:31
19:42 – 19:45	1.051	19:43
21:24 – 22:12	1.096	21:38
22:22 – 22:25	0.955	22:25
22:44 – 22:52	0.954	22:52
23:09 – 23:21	0.954	23:09
23:57 – 23:59	1.057	23:59

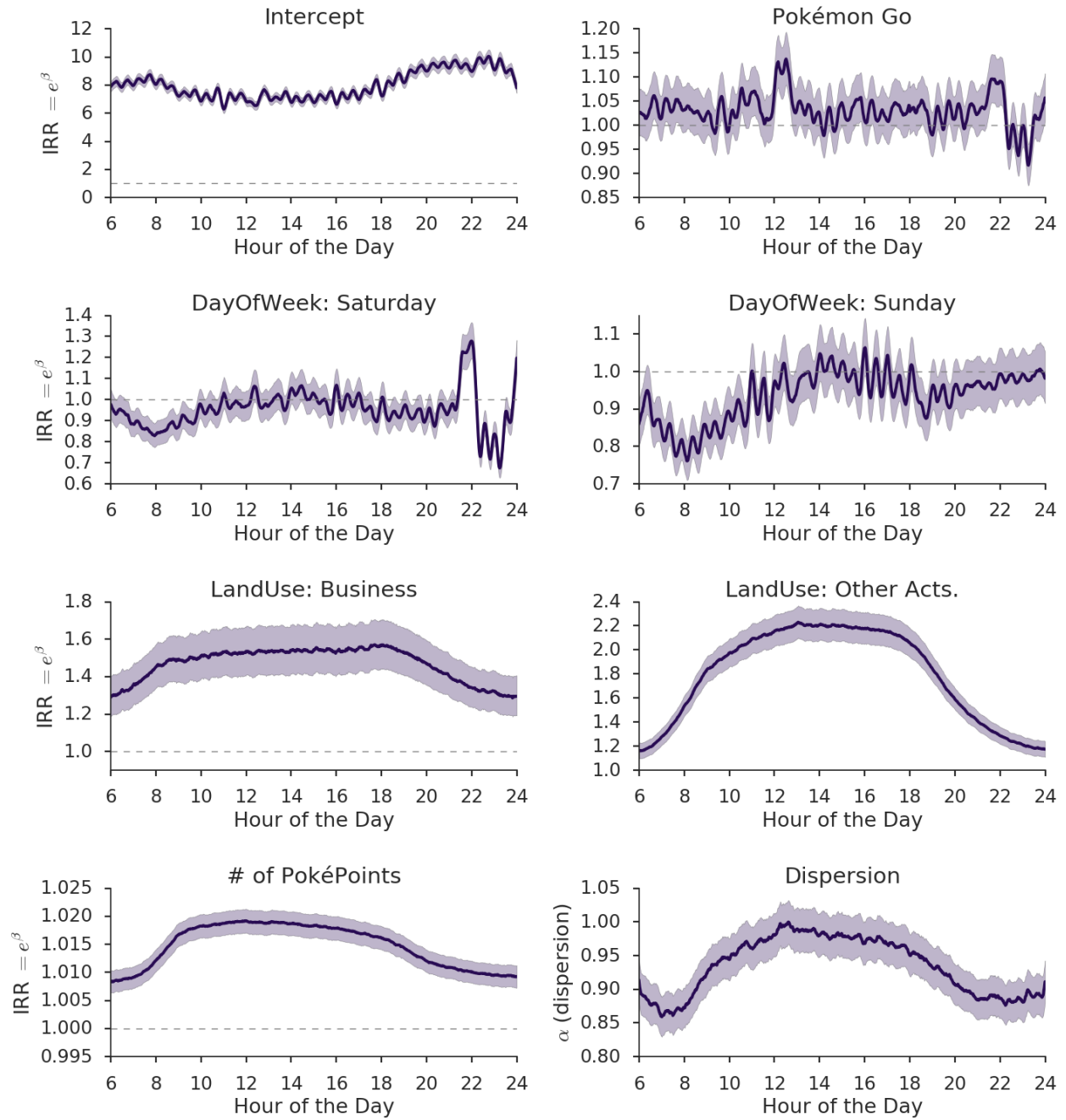


Figure 4: Covariates and dispersion (α) for each Negative Binomial regression applied to the 1-minute snapshots.

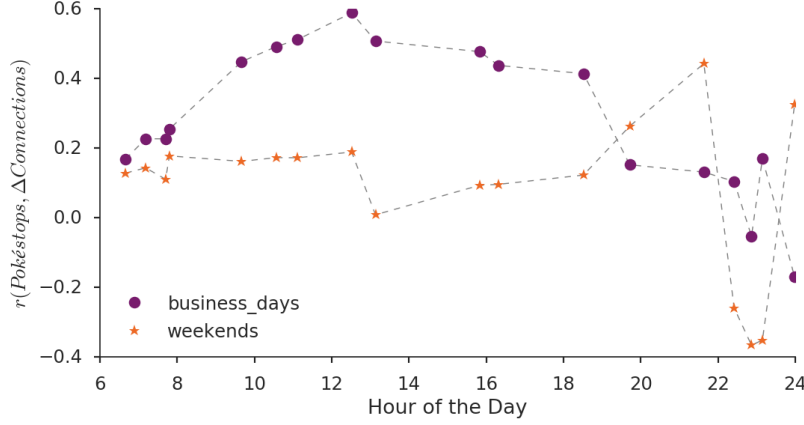


Figure 5: Normalized amount of connected devices, per minute, for all days in the dataset.

respectively. This means that, having all other factors held equal, the availability of the game increased the amount of people connected to mobile towers in the city by 13.8% at lunch time and 9.6% at night.

Finally, note that we tested statistical interactions between the regressions factors, but the interactions were not significant. Additionally, we tested the model without the covariates, having only the intercept and the Pokémon effect. Particularly, the greater time-windows presented similar results and lengths, indicating that the model is robust.

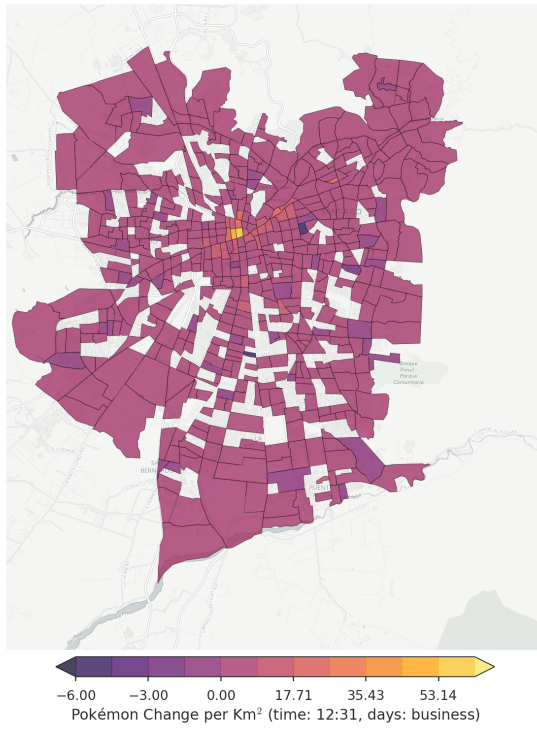
Explaining the Pokémon Go Effect. Given the specification of our model, our results are city-wide. To explore results at a finer geographical level, we estimated the first differences between two time-series: the mean of connection counts per zone after and before the launch of the game. We do so separating observations between business days and weekends. Then, we adjusted the time-series according to the surface area of each zone. We obtained time-series per zone that indicate whether they had, in average, more or less people connected within them after the launch of the game.

Our first exploration is to find whether these differences are correlated with the number of PokéPoints per square kilometers in each zone. Hence, we performed a Pearson correlation for all the minutes of the day with maximum IRR values (see Table 1). These correlations vary during the day, as shown on Figure 5. One can see that for business days the highest correlation was found at 12:31 ($r = 0.59$, $p < 0.001$). For weekends, the highest correlation was found at 21:38 ($r = 0.44$, $p < 0.001$). This would mean that the effect is stronger at lunch time at business days, and at night at weekends.

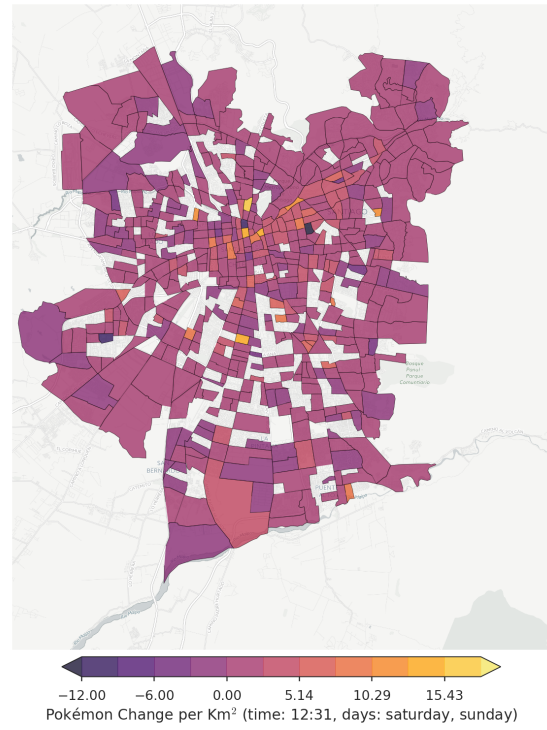
Figure 6 displays four choropleth maps of Santiago. The top row contains two maps, both showcasing first differences per zone at 12:31. The left map ((a)) displays business days, and the right ((b)) displays weekends. Similarly, the bottom row displays differences at 21:38 (business days at ((c)), weekends at ((d))). Regarding the correlations described in Figure 5, one can see that Fig. 6 (a) shows a highly concentrated effect in the city’s downtown. Reportedly this place is one of the most visited places by players at all times of the day, both because of its location within the city, as well as the availability of PokéPoints.¹⁰ In contrast, weekends present a more diversified effect on the city, specially at night, with many areas showing highly positive differences. A careful exploration of the map ((d)) reveals that zones with higher differences contain or are nearby parks and public plazas.

Next, we compare how the significant time windows of the Pokémon Go effect relate to urban mobility. We do so by graphically comparing their positions and lengths in comparison to the trip start time distribution from the OD survey. Figure 7 shows the significant time windows of the Pokémon Go effect and the trip distribution. One can see that before 6pm, which marks the end of laboral hours, the Pokémon Go effect tends to occur at moments where people starts to or is commuting, either because they are going to work or because they are taking a break. During weekends, where daily routines are not as strong and there is more flexibility, this relation is not present: the *saturday night* effect shown in Figure 4 is not present on the trip distribution.

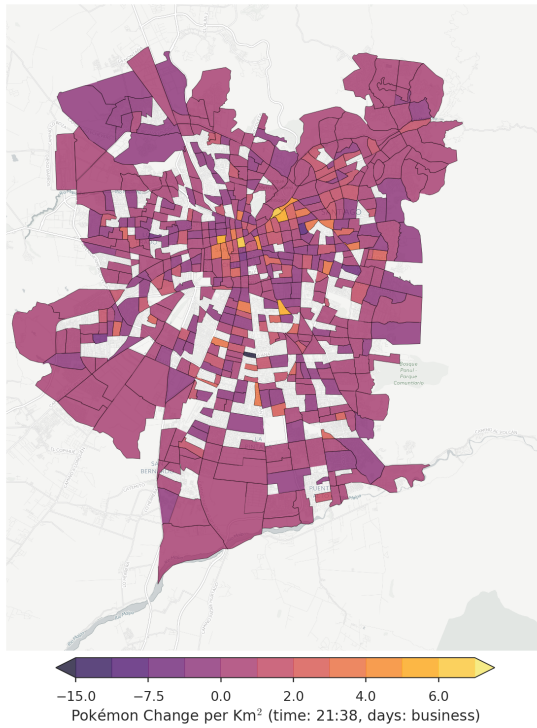
¹⁰<https://goo.gl/RcxkVA>



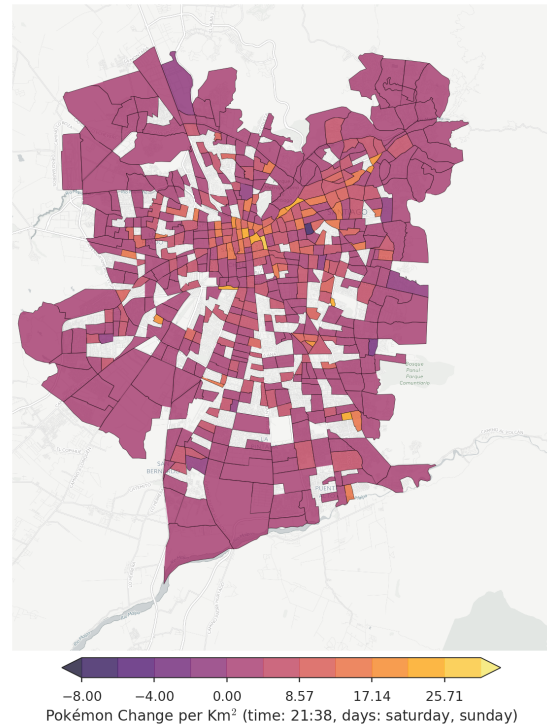
(a) Business Days. 12:31



(b) Weekends. 12:31.



(c) Business Days. 21:38.



(d) Weekends. 21:38.

Figure 6: Choropleth maps of the first differences between the means of connected devices per zone, before and after the launch of Pokémon Go. The differences are adjusted by zone area, and consider business and weekend days as different groups. A zone with a value of 0 did not show differences between periods.

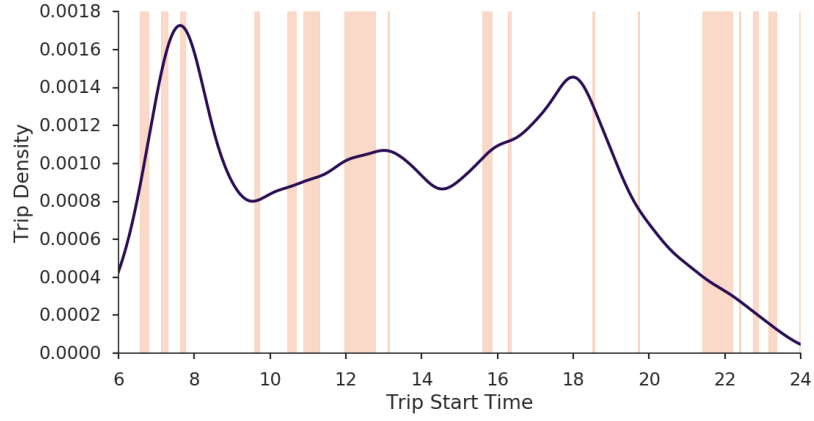


Figure 7: Distribution of trip start time according to the travel survey held in Santiago in 2012. Each rectangle shows the time-window in which the Pokémon Go effect is significant in the regression models.

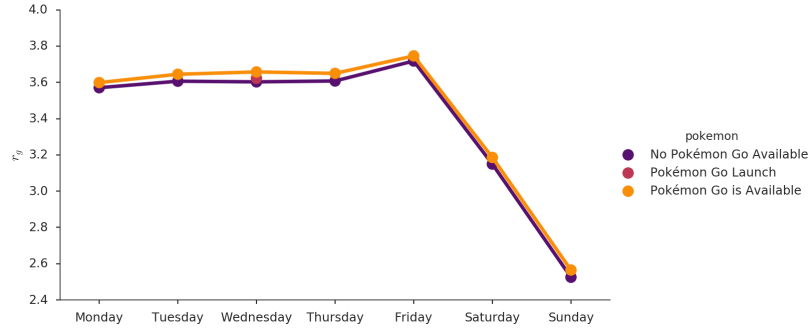


Figure 8: Daily means of the radius of gyration, having into account whether the day is before, during, or after the launch of Pokémon Go.

Table 2: Differences in radius of gyration before and after the launch of Pokémon Go. All the t -tests showed significant differences at $p < 0.001$.

Day of Week	μ_{r_g} before	σ	μ_{r_g} after	σ	Diff. (meters)	t -Test Rel.
Monday	3.57	2.74	3.60	2.75	28	-4.62
Tuesday	3.61	2.76	3.64	2.76	38	-6.27
Wednesday	3.60	2.76	3.66	2.76	54	-8.28
Thursday	3.61	2.76	3.65	2.77	41	-6.52
Friday	3.72	2.75	3.75	2.76	27	-4.21
Saturday	3.15	2.73	3.19	2.75	36	-4.10
Sunday	2.53	2.56	2.57	2.59	39	-4.59

Finally, we explore whether the Pokémon Go effect is related to urban mobility metrics. We estimated the daily average of the radius of gyration for all users under study. Figure 8 shows that there may be small differences in the daily r_g after the launch of the game on August 3rd. We performed a t -test for related samples for each day, comparing the values of r_g before and after the launch of the game. Table 2 shows the results. In summary, in all days of the week there are small significant differences in favor of Pokémon Go. The day that presents the highest difference is Wednesday (54 meters), while the day with the smallest difference is Thursday (27 meters). This supports the interpretation of people playing the game within their routines instead of altering their paths significantly. This could be expected due to human trajectories being resistant even to natural disasters [28].

4 Discussion

In this section we discuss the results shown previously. We proposed a method to perform a natural experiment at city-scale, by comparing the behavior of a subset of the population before and after the launch of Pokémon Go in Santiago. We found that the availability of the game increased the number of people that connected to the Internet on their mobile phones by 13.8% at lunch time and 9.6% at night. A further exploration of urban mobility patterns and the relations between mobile connectivity and points of interests revealed that there are two primary ways in which the effect is noticeable. On the one hand, people take advantage of commuting time and breaks during the day to play. As such, players tend to be nearby their work/study places, which are concentrated on downtown. On the other hand, on weekends at night the effect is more diversified, implying that people tend to play the game in places near their homes after having dinner.

In his book “The Great Good Place”, Ray Oldenburg discussed the need for *third places* in the city: “In order for the city and its neighborhoods to offer the rich and varied association that is their promise and potential, there must be neutral ground upon which people may gather. There must be places where individuals may come and go as they please, in which no one is required to play host, and in which we all feel at home and comfortable” [37]. The concept comes from the designation of home and work (or study) as first and second places in one’s own life. But nowadays third places are facing two challenges. First, virtual worlds [50] and social networks [42] provide social infra-structure that is similar to that of third places, but without going out of the first or second place. Second, perceptions of crime and violence are making the city to feel less safe than it really is. In Santiago, this has been called *fear of life* [13]. Hence, the usage of location-based augmented reality games may help to alleviate both situations, by placing virtual worlds in the physical reality, and by motivating people to go out and walk around their neighborhoods as our results show.

Motivating the presence of pedestrians is important. For instance, a famous theory comes from Jane Jacobs, who claims that there are four conditions that must be met for a city to be lively and safe. These conditions are: the presence of pedestrians at different times of the day, the availability of mixed uses in districts, the mixture of old and new buildings, and the availability of many crossings for pedestrians [22]. Even though testing those theories is difficult, such endeavors have been made. For instance, the city of Seoul found that the theories were valid by using house-hold surveys [51]. Recently, mobile communication records have been used to validate Jacobs’ theories in Italian cities [14]. Because Pokémon Go has the effect of increasing the number of pedestrians on the street, it has the potential to convert the city into a third place given its social features. Thus, if, for instance, crime-data would be available on a daily basis, it could be analyzed with our results to test whether the theories hold after specific interventions. Moreover, these results can be visualized. As our figures have shown (cf. Fig. 6), our method is able to produce maps apt for *patch dynamics* visualization to monitor population density [41].

Studies like those mentioned above [14, 51] perform an ex-post analysis of whether lively places comply with theories. A more granular approach would be to perform natural experiments like ours. To the extent of our knowledge, this is the first natural experiment performed using mobile records of data-type. Our method makes possible to measure the effect not only of long-term interventions, but also short-term ones, opening a path to quantify how much specific actions help to improve quality of life in the city.

Limitations. The main limitation in our study is the lack of application usage identification. Thus, even though we included several covariates in our model to account for other effects, we may still be confounding other effects within the Pokémon Go factor. However, our explanation of results based on mobility patterns

indicates that our results are coherent with what could be expected from the game’s context.

Another limitation that critics may notice is that there could be a novelty effect in our findings, in the sense that not all Pokémon Go players from the first days were engaged with the game later. Indeed, the number of Pokémon Go players has diluted enormously. While the novelty effect might be true, our study is not aimed at evaluating the popularity of the game. Instead, its purpose is to quantify the city-level effects. Given the massive popularity of the Pokémon brand, and its cultural impact in many parts of the world, we believe that the found effects represent the upper bound of mobility change in the city. In fact, in some countries Pokémon Go reached engagement rates that surpass those of mainstream social platforms like Twitter and Facebook.¹¹ In this regard, one interesting aspect of Chile is that the game was highly anticipated by the users and the media, because it was released almost one month later than in other countries like the USA. Having that in mind, the novelty effect could have helped us to reach our goal.

Future Work. We will work on user modeling and classification to see whether we can identify Pokémon players. This will allow us to study the individual effects of the game. This can be done, for instance, by estimating their daily routines using methods like [6, 19]. We can check if they visited unknown places, or whether they took more time in their trips due to the game. Additionally, this would enable an epidemiological analysis of player behavior [24], to evaluate whether social interactions influence city exploration. This is due to the Team Battle Dynamics featured in the game. Finally, we will study whether the effect of the game is correlated with crime-rate reduction in public places.

5 Related Work

Mobile Phone Data Analysis. Our work builds on extensive literature about analysis of mobile records (see [4] for a comprehensive survey). In order to analyze our data, we borrow the concept of a “snapshot”, *i. e.*, the status of the cell phone network in a specific interval of time [34]. The comparison of snapshots of the network allows to find which time instants show interesting, and, in our case, statistically significant differences. However, previous work has focused mostly on finding when the network presented higher traffic volume or population density [15], without controlling by covariates nor population size, which we do in this work. This was achieved by fixing the number of users to only those active *every single day* under study, minimizing “noise” in the form of one-off users, for instance. We also make use of the concept of *floating population profile* derived from our own, and other similar work [20, 26, 36, 43, 48, 52]. An interesting result is that this line of research has proven consistent across different cities, allowing urban planners to compare cities with respect to their land use patterns [26], as well as to study how rhythms of life differ according to socio-cultural factors [1].

According to a recent survey for urban sensing research [9], local event analysis is a key area of mobile phone data analysis. Local events are usually defined as unusual gatherings or movements of massive amounts of people (*e. g.*, protests, emergencies, sports, natural events, etc.) [3, 8, 16, 53]. Hence, the unit of analysis is a single event with time and space constraints. Our method, instead, works at the city level without any prescribed time and location, like those above. One thing in common between our work and the cited references is that all analysis have been performed ex-post. Ex-post analysis makes it possible, for instance, to create spatio-temporal signatures of places [43]. Even though these approaches allows us to analyze and understand the city, they do not allow to measure the effect of city-scale phenomena due to their assumptions of locality.

Another relevant area is prediction and forecasting of human mobility [7, 18, 46, 47]. Predictive models [7] allow to understand distributions [18] and limits of predictability in human mobility [47]. However, those methods focus on the big picture of mobility and rely on probabilistic models. Another approach is to use regression [46], like we do. However, our method differs from that of [46] in the chosen model. Instead of using longitudinal data for one regression model, for which Poisson models are better suited [10, 46], we use many consecutive Negative Binomial models, one for each time snapshot of the network, thus avoiding violating the assumptions of the Poisson model. This was needed to control for daily rhythms [45]. As the dispersion value showcases (cf. Figure 4), the NB regression was correct choice, due to α being greater

¹¹<https://goo.gl/lqwFUb>

than 0 [11]. In our case, factors that can cause over-dispersion include aggregation and non-uniform spatial distribution of the units of analysis [27].

Augmented Reality and Location-based Games. The effects of augmented reality games and applications on the city has been anticipated for more than one decade [17, 29]. However, the limits in mainstream hardware have impeded its general implementation/adoption at different times. In terms of research, most studies about the impact of those games have been small-scale only [23]. Additionally, even though smartphone technology has allowed location-based augmented reality games to become more commonplace in the last few years, until the launch of Pokémon Go they still lacked the cultural impact needed to have a considerable effect on the city. As Frank Lantz is quoted in [2], in relation to the game PacManhattan: *“If you want to make games like this you have to work hard to recruit an audience for them, you can’t just make up something awesome and then hope that people fall into it”* [25]. Since Pokémon is one of the most successful media franchises in the world [5], it enables the unique opportunity to study both, the impact of a location-based augmented reality game, and the effect of an intervention at the city scale when it comes to population mobility.

6 Conclusions

In this paper we studied how Pokémon Go affected the floating population patterns of a city. The game has led, for the first time in human history, to massive phenomena found in many parts of the world, without relating to any cause like war, climate change, famine, violence, or natural catastrophes — which usually are the kind of urban phenomena studied, as it leads to localized manifestations in both, time and space. In this regard, to the extent of our knowledge this is the first large-scale study on the effect of augmented reality games on city-level urban mobility.

While it can be argued that most of the Pokémon Go media appearances focus on specific situations, like those related to museums, tourism, and physical activity of some players, our empirical results uncovered to which extent the availability of the game modified the number of people on the street. Even though mobile datasets are usually not public, it is becoming more common to have access to this kind of information thanks to several initiatives in opening and sharing data [9]. This kind of analysis is almost costless to perform by telecommunications companies, because mobile records like CDR are already extracted and stored for billing purposes.

We observed that Jane Jacobs theorized that the streets need more pedestrians to be safe and lively [22]. Using CDR data, it has been found that at least in some cities this is true [14]. In this aspect, the most important conclusion from our work, in terms of urbanism, is that cities may not need to change their infrastructure in the short term to motivate pedestrians to go out. A game about imaginary creatures lurking neighborhoods, collectible using cell phones, has shown that the people is willing to make streets more lively by playing a mobile game when it is possible, either when they are going to work, or when they have free time at night.

In summary, our work allows to estimate the effect of specific phenomena in the pulse of city, measured through its floating population. While we focused on Pokémon Go, given its mediatic impact and high user engagement, our methods can be used to perform other natural experiments related to urban mobility. This sheds light on the possibility of measuring the impact of city-wide interventions, and using the output to inform public policy changes.

Competing interests. The authors declare that they have no competing interests.

Acknowledgements. We thank Alonso Astroza for providing a crowdsourced list of Ingress Portals validated as Pokémon Go PokéStops and PokéGyms. The analysis was performed using Jupyter Notebooks [39], jointly with the *statsmodels* [44] and *pandas* [32] libraries. All the maps on this paper include data from ©OpenStreetMap contributors and tiles from ©CartoDB.

Author Contributions. EG and LF designed the experiment and performed data analysis. All authors participated in manuscript preparation.

References

- [1] Rein Ahas, Anto Aasa, Siiri Silm, and Margus Tiru. "Daily rhythms of suburban commuters' movements in the Tallinn metropolitan area: case study with mobile positioning data". In: *Transportation Research Part C: Emerging Technologies* 18.1 (2010), pp. 45–54.
- [2] Thomas Apperley and Dale Leorke. "From the cybercafé to the street: The right to play in the city". In: *First Monday* 18.11 (2013).
- [3] James P Bagrow, Dashun Wang, and Albert-Laszlo Barabasi. "Collective response of human populations to large-scale emergencies". In: *PloS one* 6.3 (2011), e17680.
- [4] Vincent D Blondel, Adeline Decuyper, and Gautier Krings. "A survey of results on mobile phone datasets analysis". In: *EPJ Data Science* 4.1 (2015), p. 1.
- [5] David Buckingham, Julian Sefton-Green, Anne Allison, Koichi Iwabuchi, and Joseph Tobin. *Pikachu's global adventure: The rise and fall of Pokémon*. Duke University Press, 2004.
- [6] Francesco Calabrese, Giusy Di Lorenzo, Liang Liu, and Carlo Ratti. "Estimating origin-destination flows using mobile phone location data". In: *IEEE Pervasive Computing* 10.4 (2011), pp. 0036–44.
- [7] Francesco Calabrese, Giusy Di Lorenzo, and Carlo Ratti. "Human mobility prediction based on individual and collective geographical preferences". In: *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*. IEEE. 2010, pp. 312–317.
- [8] Francesco Calabrese, Francisco C Pereira, Giusy Di Lorenzo, Liang Liu, and Carlo Ratti. "The geography of taste: analyzing cell-phone mobility and social events". In: *International Conference on Pervasive Computing*. Springer. 2010, pp. 22–37.
- [9] Francesco Calabrese, Laura Ferrari, and Vincent D Blondel. "Urban sensing using mobile phone network data: a survey of research". In: *ACM Computing Surveys (CSUR)* 47.2 (2015), p. 25.
- [10] A Colin Cameron and Pravin K Trivedi. *Regression analysis of count data*. Vol. 53. Cambridge university press, 2013.
- [11] Antoni B Chan and Nuno Vasconcelos. "Bayesian Poisson regression for crowd counting". In: *2009 IEEE 12th International Conference on Computer Vision*. IEEE. 2009, pp. 545–551.
- [12] William S Cleveland and Susan J Devlin. "Locally weighted regression: an approach to regression analysis by local fitting". In: *Journal of the American Statistical Association* 83.403 (1988), pp. 596–610.
- [13] Lucia Dammert and Mary Fran T Malone. "Fear of crime or fear of life? Public insecurities in Chile". In: *Bulletin of Latin American Research* 22.1 (2003), pp. 79–101.
- [14] Marco De Nadai, Jacopo Staiano, Roberto Larcher, Nicu Sebe, Daniele Quercia, and Bruno Lepri. "The death and life of great Italian cities: a mobile phone data perspective". In: *Proceedings of the 25th International Conference on World Wide Web*. International World Wide Web Conferences Steering Committee. 2016, pp. 413–423.
- [15] Pierre Deville, Catherine Linard, Samuel Martin, Marius Gilbert, Forrest R Stevens, Andrea E Gaughan, Vincent D Blondel, and Andrew J Tatem. "Dynamic population mapping using mobile phone data". In: *Proceedings of the National Academy of Sciences* 111.45 (2014), pp. 15888–15893.
- [16] Laura Ferrari, Marco Mamei, and Massimo Colonna. "People get together on special events: Discovering happenings in the city via cell network analysis". In: *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2012 IEEE International Conference on*. IEEE. 2012, pp. 223–228.
- [17] Martin Flintham, Steve Benford, Rob Anastasi, Terry Hemmings, Andy Crabtree, Chris Greenhalgh, Nick Tandavanitj, Matt Adams, and Ju Row-Farr. "Where on-line meets on the streets: experiences with mobile mixed reality games". In: *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM. 2003, pp. 569–576.
- [18] Marta C. Gonzalez, Cesar A. Hidalgo, and Albert-Laszlo Barabasi. "Understanding individual human mobility patterns". In: *Nature* 453.7196 (2008), pp. 779–782. DOI: [10.1038/nature06958](https://doi.org/10.1038/nature06958).

- [19] Eduardo Graells-Garrido and Diego Saez-Trumper. "A day of your days: estimating individual daily journeys using mobile data to understand urban flow". In: *Proceedings of the Second International Conference on IoT in Urban Space*. Urb-IoT '16. 2016.
- [20] Eduardo Graells-Garrido, Oscar Peredo, and José García. "Sensing urban patterns with antenna mappings: the case of Santiago, Chile". In: *Sensors* 16.7 (2016), p. 1098.
- [21] William Greene. "Functional forms for the negative binomial model for count data". In: *Economics Letters* 99.3 (2008), pp. 585–590.
- [22] Jane Jacobs. *The death and life of great American cities*. Vintage, 1961.
- [23] Nicole Kosoris and Jeff Chastine. "A study of the correlations between Augmented Reality and its ability to influence user behavior". In: *Computer Games: AI, Animation, Mobile, Multimedia, Educational and Serious Games (CGAMES), 2015*. IEEE. 2015, pp. 113–118.
- [24] Martin Kulldorff. "Statistical methods for spatial epidemiology: tests for randomness". In: *GIS and Health* (1998), pp. 49–62.
- [25] Frank Lantz. "PacManhattan". In: *Space Time Play* (2007), pp. 262–263.
- [26] Maxime Lenormand, Miguel Picornell, Oliva G Cantú-Ros, Thomas Louail, Ricardo Herranz, Marc Barthelemy, Enrique Frías-Martínez, Maxi San Miguel, and José J Ramasco. "Comparing and modelling land use organization in cities". In: *Royal Society Open Science* 2.12 (2015), p. 150449.
- [27] Andreas Lindén and Samu Mäntyniemi. "Using the negative binomial distribution to model overdispersion in ecological count data". In: *Ecology* 92.7 (2011), pp. 1414–1421.
- [28] Xin Lu, Linus Bengtsson, and Petter Holme. "Predictability of population displacement after the 2010 Haiti earthquake". In: *Proceedings of the National Academy of Sciences* 109.29 (2012), pp. 11576–11581.
- [29] Carsten Magerkurth, Adrian David Cheok, Regan L Mandryk, and Trond Nilsen. "Pervasive games: bringing computer entertainment back to the real world". In: *Computers in Entertainment (CIE)* 3.3 (2005), pp. 4–4.
- [30] Marta Majorek and Marta du Vall. "Ingress an example of a new Dimension in entertainment". In: *Games and Culture* (2015), p. 1555412015575833.
- [31] Huina Mao, Xin Shuai, Yong-Yeol Ahn, and Johan Bollen. "Quantifying socio-economic indicators in developing countries from mobile phone communication data: applications to Côte d'Ivoire". In: *EPJ Data Science* 4.1 (2015), pp. 1–16.
- [32] Wes McKinney *et al.* "Data structures for statistical computing in Python". In: *Proceedings of the 9th Python in Science Conference*. Vol. 445. 2010, pp. 51–56.
- [33] Kyle Moore. "Painting the town blue and green: Curating street art through Urban mobile gaming". In: *M/C Journal* 18.4 (2015).
- [34] Diala Naboulsi, Razvan Stanica, and Marco Fiore. "Classifying call profiles in large-scale mobile traffic datasets". In: *IEEE INFOCOM 2014-IEEE Conference on Computer Communications*. IEEE. 2014, pp. 1806–1814.
- [35] John A Nelder and R Jacob Baker. "Generalized linear models". In: *Encyclopedia of statistical sciences* (1972).
- [36] Anastasios Noulas and Cecilia Mascolo. "Exploiting FourSquare and cellular data to infer user activity in urban environments". In: *Mobile Data Management (MDM), 2013 IEEE 14th International Conference on*. Vol. 1. IEEE. 2013, pp. 167–176.
- [37] Ray Oldenburg. *The great good place: cafes, coffee shops, community centers, beauty parlors, general stores, bars, hangouts, and how they get you through the day*. New York: Paragon House, 1989.
- [38] Michela Papandrea, Matteo Zignani, Sabrina Gaito, Silvia Giordano, and Gian Paolo Rossi. "How many places do you visit a day?" In: *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013 IEEE International Conference on*. IEEE. 2013, pp. 218–223.
- [39] Fernando Pérez and Brian E Granger. "IPython: a system for interactive scientific computing". In: *Computing in Science & Engineering* 9.3 (2007), pp. 21–29.

- [40] Olga Lucia Puertas, Cristian Henríquez, and Francisco Javier Meza. "Assessing spatial dynamics of urban growth using an integrated land use model. Application in Santiago Metropolitan Area, 2010–2045". In: *Land Use Policy* 38 (2014), pp. 415–425.
- [41] R Pulselli, P Ramono, Carlo Ratti, and E Tiezzi. "Computing urban mobile landscapes through monitoring population density based on cellphone chatting". In: *Int. J. of Design and Nature and Ecodynamics* 3.2 (2008), pp. 121–134.
- [42] Valentina Rao. "Facebook Applications and playful mood: the construction of Facebook as a third place". In: *Proceedings of the 12th international conference on Entertainment and media in the ubiquitous era*. ACM. 2008, pp. 8–12.
- [43] Jonathan Reades, Francesco Calabrese, and Carlo Ratti. "Eigenplaces: analysing cities using the space-time structure of the mobile phone network". In: *Environment and Planning B: Planning and Design* 36.5 (2009), pp. 824–836.
- [44] Skipper Seabold and Josef Perktold. "Statsmodels: Econometric and statistical modeling with Python". In: *Proceedings of the 9th Python in Science Conference*. 2010, pp. 57–61.
- [45] Andres Sevtsuk and Carlo Ratti. "Does urban mobility have a daily routine? Learning from the aggregate data of mobile networks". In: *Journal of Urban Technology* 17.1 (2010), pp. 41–60.
- [46] Masamichi Shimosaka, Keisuke Maeda, Takeshi Tsukiji, and Kota Tsubouchi. "Forecasting urban dynamics with mobility logs by bilinear Poisson regression". In: *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM. 2015, pp. 535–546.
- [47] Chaoming Song, Zehui Qu, Nicholas Blumm, and Albert-László Barabási. "Limits of predictability in human mobility". In: *Science* 327.5968 (2010), pp. 1018–1021.
- [48] Víctor Soto and Enrique Frías-Martínez. "Automated land use identification using cell-phone records". In: *Proceedings of the 3rd ACM international workshop on MobiArch*. ACM. 2011, pp. 17–22.
- [49] Erin Stark. "Playful places: uncovering hidden heritage with Ingress". In: *Social, Casual and Mobile Games: The Changing Gaming Landscape* (2016), p. 149.
- [50] Constance A Steinkuehler and Dmitri Williams. "Where everybody knows your (screen) name: Online games as "third places"". In: *Journal of Computer-Mediated Communication* 11.4 (2006), pp. 885–909.
- [51] Hyungun Sung, Sugie Lee, and SangHyun Cheon. "Operationalizing Jane Jacobs's urban design theory empirical verification from the Great City of Seoul, Korea". In: *Journal of Planning Education and Research* (2015), p. 0739456X14568021.
- [52] Jameson L Toole, Michael Ulm, Marta C González, and Dietmar Bauer. "Inferring land use from mobile phone activity". In: *Proceedings of the ACM SIGKDD international workshop on urban computing*. ACM. 2012, pp. 1–8.
- [53] Vincent A Traag, Arnaud Browet, Francesco Calabrese, and Frédéric Morlot. "Social event detection in massive mobile phone data using probabilistic location inference". In: *Privacy, security, risk and trust (PASSAT) and 2011 IEEE Third international conference on social computing (SocialCom), 2011 IEEE Third International Conference on*. IEEE. 2011, pp. 625–628.